Modelling seasonal pasture growth and botanical composition at the paddock scale with satellite imagery

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Abstract

Seasonal pasture monitoring can increase the efficiency of pasture utilization in livestock grazing enterprises. However, manual monitoring of pasture over large areas is often infeasible due to time and financial constraints. Here, we monitor changes in botanical composition in Tasmania, Australia, through application of supervised learning using satellite imagery (Sentinel-2). In the field, we measured ground cover and botanical composition over a twelve-month period to develop a supervised classification approach used to identify pasture classes. Across seasons and paddocks, the approach predicted pasture classes with 75-81% accuracy. Botanical composition varied seasonally in response to biophysical factors (primarily climate) and grazing behaviour, with seasonal highs in spring and troughs in autumn. Overall, we demonstrated that 10 m multispectral imagery can be reliably used to distinguish between pasture species as well as seasonal changes in botanical composition. Our results suggest that farmers and land managers should aim to quantify within-paddock variability rather than paddock average cover, because the extent and duration of very low ground cover puts the paddock/field at risk of adverse grazing outcomes, such as soil erosion and loss of pasture biomass, soil carbon and biodiversity. Our results indicate that satellite imagery can be used to support grazing management decisions for the benefit of pasture production and the improvement of environmental sustainability.

Key words: Pasture management, Supervised classification, Sentinel-2, grazing system modelling, ecosystem, dry matter digestibility, pasture quality, grazing preference

1. Introduction

Pasture botanical composition is directly linked with overall sward productivity, with productivity varying seasonally according to pasture ecotype, resource availability and phenology. In some cases, swards with diversified botanical composition that include grasses, legumes and herbs may be more drought tolerant and prevent weed incursions (Bell et al., 2015; Pembleton et al., 2016; Sanderson et al., 2005) Quantification and monitoring of botanical composition may thus translate to sward productivity, having implications for livestock feed supply.

Increasing livestock utilisation (consumption) of pastures often directly translates with increased profitability, because vegetative biomass is one of the cheapest forms of feed (Chang-Fung-Martel et al., 2018; Harrison, Cullen, Tomkins, et al., 2016; Harrison, Evans, et al., 2012a, 2012b; Ho et al., 2014). Conventionally, pasture quanta and botanical composition of intensively grazed pastures in southern Australia have been assessed visually, with farm managers often relying on knowledge gained through their own heuristics or professional networks to distinguish between pasture species. Although ground-based methods are useful for pasture monitoring over small scales, such methods are often laborious, time consuming and sometimes expensive (Alcock et al., 2015; Harrison, Jackson, et al., 2014; Xu et al., 2008). Reliable botanical composition classification can be further hindered by substantive pasture variation within a paddock, increasing the number of assessments required to gain an accurate measure of intra-paddock pasture variability.

Remote sensing and Geographic Information System (GIS) approaches coupled with predictive algorithms may provide a viable alternative to within-field pasture monitoring and pasture species classification (Ali et al., 2016). For example, various authors have used satellite imagery time series (moderate resolution imaging spectroradiometer - MODIS; NOAA advanced very high-resolution radiometer (AVHRR) and Landsat) to obtain vegetation indices and phenological metrics to help understand pasture condition (Aguiar et al., 2010; Davidson, 2008; Müller et al., 2015) and pasture biomass quanta (Barrachina et al., 2015; Hanna et al., 1999; Jin et al., 2014; Kogan et al., 2004; Shuang et al., 2012; Wylie et al., 1991; Xu et al., 2008). Zengeya et al. (2013) used WorldView-2 multispectral imagery to map pasture quality and showed that such imagery enhanced pasture quality estimation and mapping. Schaefer and Lamb (2016) used vehicle-mounted light detection and ranging (LiDAR) measurements to improve estimation of pasture biomass and found that combined LiDAR and active optical reflectance sensors contributed to better estimation of pasture biomass. However, many of these approaches do not have either the temporal (sub-weekly) or spatial (< 20 m^2) resolution necessary to enable pasture species cover or botanical composition quantification to provide information of sufficient resolution to facilitate grazing management decision making at the paddock level.

Sensors carried by hand, land or aerial vehicle have been used to distinguish between pasture species at the paddock level. For example, multispectral and hyper spectral sensors as well as multi-spectral radiometers have been used to assess pasture quality with reasonable reliability over a small area (Cletah & Onisimo, 2017b; Pullanagari, 2011; Pullanagari et al., 2012). These studies have shown that pasture quality can be predicted using non-destructive sampling. It remains to be seen whether multispectral imagery from satellite can be used to monitor pasture cover and botanical composition over an extended duration (several months or years) at paddock/field scales (e.g. 50-100 ha).

Satellite imagery research on pastures has classically been aimed at much larger scales such as the regional, continental or global levels (Crabbe et al., 2020; Vickery et al., 1997). With the rise of cloud computing, big data analytics and machine learning (Belgiu & Drăguţ, 2016; Mountrakis et al., 2011; Pal, 2005; Pal & Mather, 2003), vegetation classification for specific contexts has increased in popularity, including supervised classification of pixels (Baldi et al., 2006; Gómez et al., 2016; Miehe et al., 2011; Reiche et al., 2012; Toivonen & Luoto, 2003; Weiers et al., 2004) and Maximum Likelihood Classifiers (MLC). Despite this, reliable prediction of pasture and other vegetation cover at the regional scale have had limited success due to lack of ability to distinguish between land-cover attributes (Brenner et al., 2012; Rufin et al., 2015). Such results suggest a need to mask non-pasture features (e.g. trees, fences, water bodies, infrastructure etc.) in studies that aim to distinguish between pasture species at the paddock level. Other studies using multispectral optical imagery have been conducted to distinguish between pasture functional types (C3 and C4 species) (Cletah & Onisimo, 2017a, 2017b; Liu et al., 2015); such studies have been performed using a wide array of techniques (e.g. Discriminant Analysis, Support Vector Machine) with accuracy ranging from 82-98%, but in most cases have again been conducted at scales much larger than a paddock/field. Taken together, such studies highlight a dearth of information relating to the reliability and practicality of using multispectral imagery to assess pasture cover and composition at the paddock scale using simple classifiers such as MLC.

The inception of the Sentinel-2 satellite constellation (ESA, 2020) provides a unique opportunity to analyse changes in pasture cover and composition at spatial and temporal scales sufficient for decision-making at the paddock scale. We hypothesised that high-resolution multispectral data from Sentinel-2 could be used to model seasonal changes in pasture growth and composition at the paddock scale (i.e. 50-100 ha). Our objectives were thus to (i) characterise spatial pasture variability at the paddock level and (ii) use supervised classification to map key pasture species classes and observe how such classes change seasonally.

2. Materials and methods

2.1 Study area

The study was located at Triabunna, Tasmania, Australia (Figure 1). Triabunna has a cool maritime climate; mean monthly temperature oscillates from a minimum of 6.8°C in July to a maximum of 16.8°C in January; rainfall is equi-seasonal with monthly and annual average values of 56 mm and 665 mm respectively (BoM, 2020). Soils on the study area were primarily brown Chromosols and Eutrophic Brown Dermosols (DPIPWE, 2000; Isbell, 2016), while topography varied from undulating to hilly. Field samples collected on a commercial wool enterprise on four case study paddocks: Balsey Hill (67.52 ha), Cottage Hill (118.6 ha), Bouganville (58.3 ha), and Lords (73.62 ha) (Figure 1, shaded areas).

<Insert Figure 1>

Figure 1. Location of study area including individual paddock boundaries and paddock names, shaded areas represent study paddocks. The left-hand panel shows the farm location in the Australian State of Tasmania.

2.2 Field measurement of pasture types and satellite image dates

Field measurement of pasture cover following Anderson et al. (2011) were collected in the study paddocks during 2019 and 2020 (Table 1). Dates of field measurements were aligned with the nearest Sentinel-2 image date (Table 1). Locations of field measurements were undertaken with a multi-satellite handheld GPS unit (GARMIN GPS MAP 66S GPS DEVICE) with ~2 meter accuracy. Pasture growth and botanical composition was monitored for three-month periods, including summer (Dec-Feb), autumn (Mar-May), winter (Jun-Aug), and spring (Sep-Nov). Summer starts in December and finishes in February in the following year (e.g. 'summer 2017/18' is the summer adjoining 2017 and 2018.

Table 1: Seasonal alignment of field measurements with Sentinel-2 image dates

Season	Field measurement periods	Sentinel-2 image date
Winter 2019	13-29 August 2019	23 August 2019
Spring 2019	15-18 October 2019	22 October 2019
Summer 2019/20	7-12 January 2020	30 January 2020
Autumn 2020	24-27 April 2020	24 April 2020
Winter 2020	24-29 July 2020	23 July 2020

To enable repeated measurements over the course of the experiment on the same points, field measurements were conducted visually following Tothill et al. (1992) and Waite (1994). Botanical composition was measured in the field using 100 mm × 100 mm quadrats placed on the same latitude and longitude for each temporal measurement shown in Table 1. Measurement points were conducted across a range of botanical compositions, topographies and soil types to gauge the full spectrum of biophysical conditions (Figure 2).

<Insert Figure 2>

Figure 2. Sentinel-2 images (true colour, red, green, and blue) of study paddocks: Balsey Hill, Cottage Hill, Bouganville, and Lords on 22 October 2019. Locations of field measurements are indicated by red dots (dot size not drawn to scale). Non-pasture areas including trees, bush, wetlands, and non-grazing areas were excluded from the analysis (white areas within the paddock). Image acquired in July 2020.

Pasture botanical composition consisted of introduced and native pasture ecotypes in the study area (Table 2). Improved pasture species were those sown in the study paddocks and sourced from commercial pasture seed suppliers. Botanical composition measured in the field were thus grouped into improved, native, or mixed, with improved and native classes having a minimum of 20% of the said botanical composition and ‘mixed’ having 20% minimum of both improved and native classes. Each point was also subject to a 30% minimum green cover threshold to ensure botanical composition spectra were sufficient to enable classification and prediction from satellite imagery.

Table 2. Native and introduced pasture species used in this study. A third pasture class (mixed pasture species) was defined as having a minimum of 20% of both improved and native species.

Improved species	**Native species**
Phalaris (*Phalaris aquatica*)	Kangaroo grass (*Themeda triandra*)
Cocksfoot (Dactylis glomerata)	Wallaby grass (*Austrodanthonia caespitosa*)
Perennial ryegrass (*Lolium perenne*)	Silver tussock grass (*Poa labillardierei Steud.*)
Fescue (*Festuca arundinacea*)	
Subterranean clover (*Trifolium subterraneum*)	

2.3 Sentinel-2 image analysis

Sentinel imagery were downloaded from the European Space Agency (ESA) Scientific Hub in May-July, 2020 (ESA, 2020). Sentinel 2A (S2A) was launched on 23 June 2015 and Sentinel 2B (S2B) on 7 March 2017, with images generated every 10 days from 2015 to present. We considered Level 1C Top of Atmosphere (TOA) images from December 2017 (summer 2017/18) to monitor seasonal pasture growth (see Table S1). Sentinel-2 S2A and S2B used in the present analysis were based on proximity of the image acquisition date with the corresponding field measurement date (Table 1) to classify botanical composition. Only cloud-free images at the paddock scale were used: top of atmosphere (TOA) images were ortho-rectified, radiometrically and geometrically corrected in the ESA hub. The Sentinel-2 Multispectral Instrument (MSI) comprises 12 spectral bands, ranging from Visible and Near-Infrared (VNIR) to Shortwave Infrared (SWIR) wavelengths along a 290 km orbital swath, of which there are four VNIR bands (B2, B3, B4, and B8) at 10 m, four red edge bands (B5, B6, B7, B8a) and two SWIR bands (B11 and B12) at 20 m, and three other bands (aerosol, water vapour, cirrus SWIR B1, B9, and B10 respectively) at 60 m resolution (Table S2).

The study workflow is shown in Figure 3. Input data are described above. In the processing stage, we stacked all bands and resized images at 10 m resolution using the nearest neighbour algorithm. We masked images at the paddock level (Figure 2) to calculate NDVI; these data were collected from January 2018 to February 2020 using the AgroInsider platform (AgroInsider, 2020). We defined field data using botanical composition and percentage cover of pasture species as Improved (I), Native (N) and Mixed (M) (Table 2). In the analysis stage, we developed training data based on TOA reflectance for each pasture species class and used these data to perform Maximum Likelihood Classification (MLC). Refined field data were then used for accuracy assessment of the predictive MLC outcomes. Seasonal changes in botanical composition were examined by running several MLC and developing a spectral library (based on the training data developed in the analysis stage). Seasonal botanical composition changes are presented over five seasons (winter 2019-winter 2020) (Table 1).

<Insert Figure 3>

Figure 3. Schematic of study workflow. Input data includes 12 top of atmosphere (TOA) bands from Sentinel-2 and field samples. Processing included stacking of bands, paddock-level masking and refining the field sampling. Analysis included model calibration, supervised classification and accuracy assessment, while change detection included development of the spectral library and identification of botanical composition changes.

We used Arc Geographic Information System (ArcGIS) 10.6 software for construction and manipulation of paddock shapefiles, including non-pasture region exclusion, resampling, layer stacking, masking, re-sizing images, layout and mapping classified images, Normalized Difference Vegetation Indices (NDVI) and the Environment for Visualizing Images (ENVI) 5.4 software for other processing, enhancement, classification, accuracy assessment

2.4 Spatio-temporal phenological variation

Intra-paddock spatial and temporal phenological variation in pasture cover was analysed using NDVI (Tucker, 1978) generated from 10 m resolution red (B4) and near-infrared (B8) spectral bands of Sentinel-2. NDVI (Eqn. 1) is a common vegetation index for studying pasture phenology (Asher et al., 2018; Bella et al., 2004; Boschetti et al., 2007; Flynn et al., 2008; Serrano et al., 2018).

$$NDVI = \frac{(NIR - red)}{(NIR + red)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (1)$$

Where *red* corresponds to band 4 (30 nm) and NIR corresponds to band 8 (842 nm) of Sentinel-2. NDVI ranges from -1 to +1, with cloud, bare soil, and sand showing negative/low NDVI (-1 to <0.1), shrubs and grasslands moderate NDVI (0.2 to 0.5) and dense vegetation/grassland high NDVI (0.6 to 0.9). Based on this classification, we divided the NDVI range 0.1-0.9 into five class, very low (<0.20), low (0.20-0.31), medium (0.31-0.35), high (0.35-0.40) and very high (>4.0) to represent distinctive NDVI variation according to these classes over study paddocks.

2.5 Botanical composition training data

Botanical composition was classified using training data approaches outlined by Roth et al (2012), Veganzones and Grana (2008), and Xu et al.(2015). Training sites were selected using a range of geolocated regions of improved, native, and mixed composition in the study paddocks. Spectra for training samples were developed for pasture classes in autumn 2020 then merged (union) to three regions of interest (ROI) representing improved, native and mixed classes (Figure 4). The same process was applied to develop ROI for winter in 2020. Eighteen and twenty training samples were developed for autumn 2020 and winter 2020, respectively. In each case, two sets of ROI pairs were used to discriminate spectra for individual pasture classes using a separability threshold (Csendes & Mucsi, 2016) of at least 1.95 for each ROI pair. Separability was computed using the Jeffries-Matusita (JM) distance and the transformed divergence algorithms computed following Richards and Richards (1999) using pasture class means and covariance matrices; a separability value of 2.0 corresponds to complete separability. Mean ROI for autumn and winter were used as a reference to develop the spectral library. Reflectance of each pixel was assumed to be linearly proportional to botanical composition (or ROI) (Quintano et al., 2012; Roberts et al., 2002). This approach was then used for pasture classification in other seasons (Table 1).

<Insert Figure 4>

Figure 4. Training spectra for botanical composition from Sentinel-2 (Image acquisition date: 24 April 2020). Twelve Sentinel-2 bands were used to collect the TOA reflectance spectra.

2.6 Maximum likelihood classification (MLC)

Supervised classification was conducted using the maximum likelihood classification (MLC) in ENVI software (Mohri et al., 2018; Russell & Norvig, 2002). MLC computes the probability that a pixel belongs to a given class (input), assuming that spectra for each class within each band are normally distributed to produce a classification map (output) (Richards & Richards, 1999). Each pixel was allocated to the class having the maximum probability (i.e., the maximum likelihood).

2.7 Accuracy assessment

Akin to model validation (Bell et al., 2015; Harrison, Evans, et al., 2012b; Harrison, Evans, & Moore, 2012; Pembleton et al., 2016), the MLC modelling approach was evaluated in ENVI using a confusion (or error) matrix accuracy assessment (Lillesand et al., 2015) by comparing modelled MLC classes to those measured on ground. Overall, 24 and 21 field measurements were used in the accuracy assessment for autumn, 2020 and winter 2020, respectively. The confusion matrix included omission errors, commission errors, producer's accuracy and user accuracy and contingency tables are presented in the supporting information related to each season. Following Congalton (1991), the Overall accuracy (O_c) were calculated for each classification using Eqn. 2.

$$O_c = \frac{\sum_i^r x_{ij}}{N} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (2)$$

Where, r represents number of rows in the non-square matrix, x_{ij} is the total number of correctly classified pixels in row i and column j.

3. Results

3.1 Seasonal paddock level pasture cover

Paddock average pasture cover was generally greatest in spring and least in autumn (Figure 5) in line with growth rates typically seen for temperate pastures (Alcock et al., 2015; Harrison et al., 2017; Harrison, Jackson, et al., 2014). This pattern was consistent across all study paddocks in 2018. Persistently dry conditions in 2019 (total rainfall in 2019 was 457 mm compared with the long-term average of 613 mm) caused greater pasture senescence and low growth rates, resulting in low ground cover in 2019 until summer 2019-2020. However, the situation improved in 2020, particularly for autumn, 2020 and winter 2020 for all study paddocks.

<Insert Figure 5>

Figure 5. Temporal variation of seasonal pasture cover based on NDVI from Sentinel-2 images from January 2018 to August 2020 (x-axis represents delineates each season) for paddocks: Balsey Hill (a), Cottage Hill (b), Bouganville (c), and Lords (d).

Seasonal and spatial variation in pasture cover during 2019 and 2020 are shown in Figure 6. All paddocks exhibited a high degree of intra-paddock pasture cover variation, indicating variability in growing conditions due to soil type, hill aspect and long-term grazing preferences, such as location with which animals camped. Figure 7 and 8 also underscore the need to quantify within paddock pasture variability in grazing management contexts, rather than paddock averages. For example, in winter and spring of 2019, pasture cover varied from less than 0.20 to more than 0.4 in all paddocks, suggesting a high degree of spatial variability in pasture cover. In general, the lowest and highest NDVI occurred in summer 2019/20 and autumn 2020, respectively, because many areas in autumn had NDVI >0.4.

<Insert Figure 6>

Figure 6. Spatial variation of seasonal pasture cover based on NDVI, derived from Sentinel-2 images for Balsey Hill (a), Cottage Hill (b), Bouganville (c), and Lords (d) paddocks.

3.2 Using supervised classification to distinguish between pasture classes

The distribution of native, introduced and mixed pasture classes were assessed at a pixel resolution of 10 m^2 using supervised classification (MLC) in autumn 2020 (Figure 7) and winter 2020 (Figure 8). The majority of native pasture classes occurred in the east of Balsey Hill (Figure 7a), in the north and centre of Cottage Hill and Lords (Figure 7b), and on the north-eastern flats of Bouganville (Figure 7c). Native pasture species tended to be more prolific around trees, shelter belts or on paddock hills. In winter, there were more introduced pastures, similar mixed and fewer native species relative to the distribution in autumn (Figure 7), indicating seasonal differences in phenology of the key pasture classes: introduced species being more dominant in winter and native species being relatively more abundant in autumn.

Accuracy of the supervised classification was assessed using the percentage of correctly classified pixels in a confusion matrix (locations of field measurements are shown in Figure 2). The supervised classification had an accuracy of 75% and 81% in autumn and winter, respectively (contingency table presented in Tables S3, S4), indicating adequate performance of the supervised classification approach in predicting pasture classes. Many of the predicted native and mixed pasture classes aligned well with the points measured on the ground, although some of the modelled improved pasture classes did not align with those measured on ground. This may be because these points were located in areas of high pasture spatial heterogeneity, making it difficult to obtain a reliable prediction of pasture classes.

To examine how pasture species distribution changed relative to previous season(s), we used the spectral library (developed based on the mean spectra for each pasture class in autumn and winter 2020) to simulate pasture species distribution winter 2019, spring 2019 and summer 2019/20 (data shown in Figure 9 and Figure S1, S2 and S3).

Overall, the supervised classification approach used here had significant ability to distinguish between native and improved ROI pairs, and between native and mixed ROI pairs, with a maximum separability threshold of 1.99 being achieved in both cases. However, the classification between improved and mixed species could be improved notwithstanding that considerable separability (1.97) between ROI pairs of these pasture classes was achieved. These results suggest that a large part of the overall accuracy obtained in the assessment (75-81%) was due to reliable classification of native and mixed pasture

<Insert Figure 7>

Figure 7. Predictions (green, blue and yellow represent improved, native, and mixed respectively) of pasture classes from the supervised classification compared with locations of measured pasture species shown by red points (I , N, and M represent improved, native, and mixed respectively) for autumn 2020 on Balsey Hill (a), Cottage Hill (b), Bouganville (c) and Lords (d).

<Insert Figure 8>

Figure 8. Predictions (green, blue and yellow represent improved, native and mixed respectively) of pasture classes from supervised classification compared with the locations of measured pasture species data shown by red points (I , N and M represent improved, native and mixed, respectively) for winter 2020 on Balsey Hill (a), Cottage Hill (b), Bouganville (c), and Lords (d).

3.3 Seasonal changes in pasture class distributions

Seasonal changes in the cumulative areas of pasture classes across all paddocks are shown in Figure 9. In autumn 2020, the improved and native pasture classes were at their highest cumulative areas of 38.2 ha and 44.7 ha respectively. The lowest cumulative area for the improved species was observed in summer 2019/20 (21.3 ha) and for the native class in winter (24.1 ha). The total area for mixed pasture classes varied little, from a maximum in winter 2019 of 156.4 ha to a minimum in autumn 2020 of 132.1 ha.

<Insert Figure 9>

Figure 9. Cumulative pasture area of all study paddocks from winter 2019 to autumn 2020. Error bars show one standard error of the mean.

4. Discussion

4.1 Quantifying intra-paddock pasture variability for sustainable grazing outcomes

Here, we used high resolution multi-spectral imagery to examine within-paddock pasture cover variability and pasture species composition. Our results show that grazing managers need to measure paddock level pasture variability (Figure 6) rather than paddock average cover, because the extent of very low ground cover (i.e. the area of ground below the paddock average) puts the paddock at risk of adverse grazing outcomes, such as soil erosion, loss of pasture biomass, soil carbon and biodiversity. Overgrazing has become an environmental concern, having adverse effects on soil erosion (Rowntree et al., 2004), soil organic matter (Conant & Paustian, 2002), increasing land degradation (Sonneveld et al., 2010) and loss of valuable biodiversity (Fedrigo et al., 2018). Budd and Thorpe (2009) indicate that appropriate grazing management leads to reproduction and regeneration of vegetation, provision of wildlife habitat and potentially greater economic benefit through natural capital. Grazing managers should thus pay attention to paddock areas with the least ground cover and manage grazing according to these areas for long-term sustainability (Chang-Fung-Martel et al., 2018).

Pasture growth rates vary due to abiotic (soil, climate, elevation) and biotic conditions (pasture genetic potential, insects and other wildlife, soil microbiota) as well as grazing management which together highlight the need for regular paddock-level pasture cover assessment (Harrison, Cullen, Tomkins, et al., 2016). In the cool temperate climates of Tasmania, pasture cover peaks in spring due to increasing seasonal warmth, high rainfall and good soil moisture conditions, and troughs in late summer/autumn due to lack of rainfall and soil moisture (Harrison, Cullen, & Rawnsley, 2016). Such trends concur with those shown in Figure 5. However, rapid decline of pasture cover that can even occur under conditions of high initial ground cover (e.g. winter 2018 in Bouganville) demonstrate the susceptibility of pasture cover to overgrazing and again underscore the need for regular monitoring of paddock conditions to ensure long-term sustainable grazing outcomes.

Our study also showed high intra-paddock spatial variation of pasture cover (Figure 6). This may be partly attributed to grazing regimes, grazing preferences including sheep camping locations, variation in pasture phenology, soil type and land elevation. Indeed, the majority of native pasture species in this study were concentrated in areas close to trees, on steep slopes, or on low lying coastal areas. In general, native pasture classes were associated with lower pasture cover while improved pasture classes were associated with higher NDVI (compare Figure 6 with Figure 7 and Figure 8). Such differences indicate that native pasture species generally had less ground cover at the time this study was conducted. Pastures with greater dry matter digestibility (DMD) per unit area will lead to greater liveweight gain and potentially profitability: higher DMD can be attained through either greater biomass, higher quality pasture or both, so ideally farmers would cultivate pastures leading to the highest DMD per hectare (Chapman et al., 2012; Harrison, Christie, et al., 2014). However, other factors, such as nutrient use efficiency and drought resilience are also important. The native grasses in this study (primarily Kangaroo grass and Wallaby grass) require no synthetic fertiliser inputs, while the improved pastures (cocksfoot, phalaris and perennial ryegrass) require nitrogen inputs for higher productivity (Christie et al., 2020; Rawnsley et al., 2020). In this case, the farm had a focus on pasture management strategies to conserve and enhance the growth and regeneration of native species due to lower reliance on synthetic fertiliser inputs (which in Australia are costly) (Hayes et al., 2019). We suggest that future work be aimed at the derivation of metrics for coupling NDVI with botanical composition to enable better understanding of relationships between spatial pasture growth and pasture species abundance. Having such knowledge would facilitate the development of pasture management strategies (e.g. fertiliser application or strategic grazing management) that may lead to desirable shifts in botanical composition.

As the majority of previous studies have focussed on assessment of pasture cover at the landscape level (Ali et al., 2016; Roberts et al., 2002; Shuang et al., 2012), the implications of grazing management decisions at the paddock level have received relatively little attention in remote sensing research. Similarly, while there are many decision-support systems to help graziers manage pastures (AgroInsider, 2020; Cibolabs, 2020; DataFarming, 2020; Decipher, 2020; Pasture.io, 2020), such tools often do not allow distinction between pasture species. Optical remote sensing may provide an opportunity for pasture classification analysis (Congalton, 1991; Khatami et al., 2016; Vickery et al., 1997). Employing MODIS and enhanced thematic mapper plus (ETM+), Liu et al.(2015) used time-series NDVI to classify C3 and C4 features with 86% accuracy. Other work has used discriminant analysis to compare imagery from Landsat 8 OLI, Sentinel-2 and Worldview 2 to discriminate between C3 and C4 grass species and has found varying levels of accuracies across sensors and seasons, ranging from 86% to 100% (Cletah & Onisimo, 2017a, 2017b). Similarly, our analysis showed that MLC with Sentinel-2 allows reasonable prediction of pasture classes at the paddock scale.

Here, our analysis was performed with partial ground cover such that leaf area index was never greater than 3.0. Such leaf areas are common to many extensive grazing zones in Australia. Areas with leaf area indices greater than 3.0 (or when pasture dry matter greater is than 3,000 kg DM/ha), synthetic aperture radar imagery (SAR) may offer a way forward. Indeed, the number of studies conducted using SAR to analyse physical characteristics of pasture such as canopy height continues to grow (Crabbe et al., 2020; Crabbe et al., 2019; Dos Reis et al., 2020; Hill et al., 2005). In recent studies, such approaches have been conducted with reasonable accuracy (e.g. 68-84% (Crabbe et al., 2019) and have been further improved by combining SAR with optical data (87-93% accuracy, (Crabbe et al., 2020)). Using imagery from Sentinel-1, Crabbe et al. (2020) also showed that support vector machine (SVM, a form of machine learning) outperformed the MLC approach used here, as well as a random forest approach. Such results suggest that future studies of this type could trial the SVM as a classification method for distinguishing botanical composition.

4.2 Prospects for pasture botanical composition diagnosis using remote sensing

We showed that the spectral signature of native grass was distinct compared with that of the improved and mixed species. A similar result was confirmed by Shoko and Mutanga (2017b), who found that the spectral signature (wavelength) of native *Themeda* grass was higher than that of *Festuca*, especially in summer. This indicates that native species morphology and physiology is more identifiable than (the difference between) improved and mixed species classes. This observation may be due to differences in leaf nitrogen or pigmentation between species and thus spectral reflectance (Adjorlolo et al., 2014; Adjorlolo et al., 2015; Walburg et al., 1982).

Successful discrimination of botanical composition has positive ramifications for biodiversity assessment, habitat management and ecosystem services (Dorrough et al., 2004; Sanderson et al., 2013; Weibull et al., 2003). Austrheim and Eriksson (2001) showed that remote sensing information on sheep/cattle densities, wildlife densities and soil characteristics can influence species diversity and have implications for sustainable grazing management. Distinguishing botanical composition may also help manage and maintain natural capital (the economic value provided by wildlife, provision of habitat), because areas with native pasture species may have greater soil carbon stocks compared with areas with improved species (Chan et al., 2010). Ultimately the approach outlined here is conducive to greater insight into biodiversity, natural capital, and habitat management, which together potentially enhance the prospects for regenerative agriculture.

As more high-resolution optical satellite imagery becomes available, our approach could be further refined and implemented using imagery with greater spatial and temporal resolution (e.g. using the Planet CubeSat satellite constellation (Planet, 2020). Such information would be expected to increase analytical quality in paddock level monitoring (Dos Reis et al., 2020). As well, the combination of SAR and optical data with different machine learning techniques (e.g. SVM) may provide further insights into pasture attributes. Combining satellite-based approaches with hyperspectral imagery collected using Unmanned Ariel Vehicle Systems (UAVS) (Melville et al., 2019; Psomas et al., 2011) may also add value, though labour complexity in such cases may also increase (indeed, a key advantage of system is the low requirement for physical input from the grazing manager).

5 Conclusions

We demonstrated that the combination of Sentinel-2 imagery and supervised learning is a viable approach to quantify seasonal pasture ground cover and botanical composition. Greater performance can be anticipated when more field measurements become available for training and enable the use of more complex, data-intensive supervised classifiers. Although pasture cover varied seasonally in line with changes in climate and grazing management, paddock level changes in pasture species distribution were able to be reliably monitored. Overall, our results could be used to enact more timely grazing management as well as tactical farming approaches, such as conservation of native pasture species when ground cover is low. Such approaches would be expected to improve ground cover, reduce soil erosion, improve soil carbon stocks and biodiversity values. Improvement of natural capital in this way would be expected to improve long term sustainability and profitability.

Author Contributions

Conceptualisation: IA and MTH; Method: IA, MTH, and JW; Data/Image collection: IA, JW, KB, LG, JMDS, and FM; Data/Image analysis: IA; Original draft preparation: IA; Review and editing: MTH, JW, FW, KB, and LG; Funding acquisition: JW, MTH.

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Conflicts of Interest

The authors declare no conflict of interest.

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Figure 1

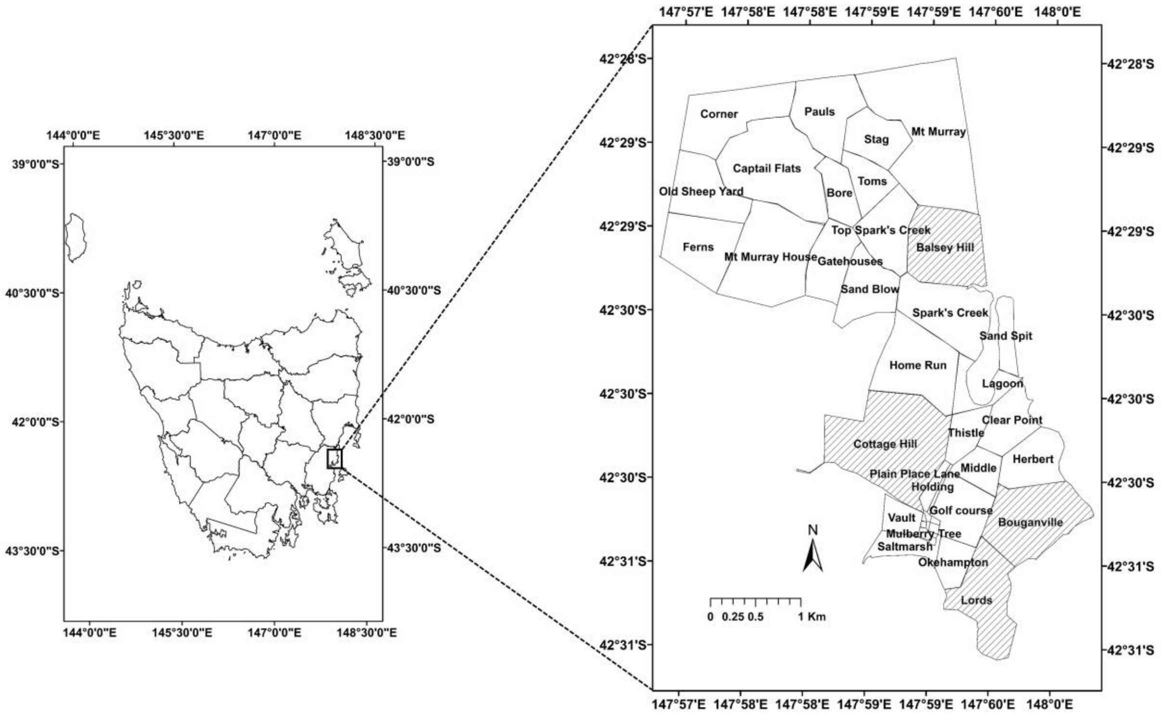

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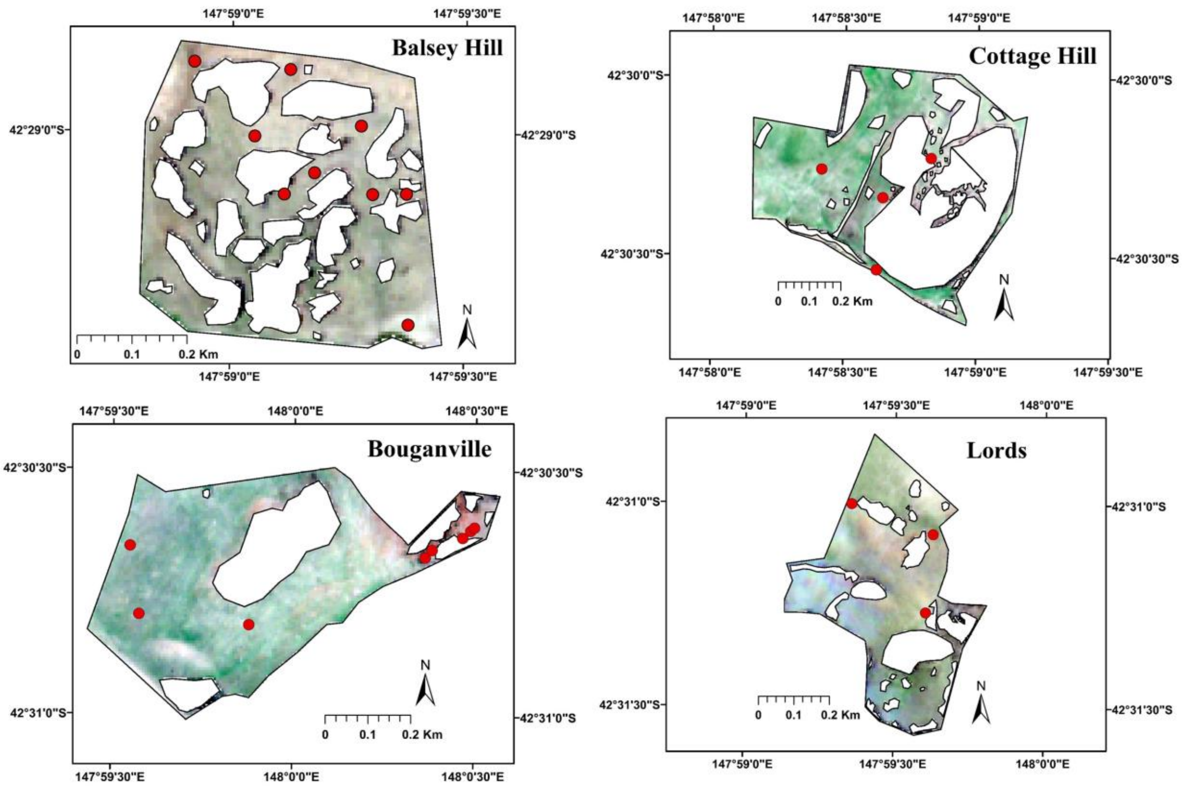
Figure 2



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147°59'0"E
147°59'30"E
42°29'0"S
0
0.1
0.2 Km
N
Cottage Hill
147°58'0"E
147°58'30"E
147°59'0"E
147°59'30"E
42°30'0"S
42°30'30"S
Bouganville
147°59'30"E
148°0'0"E
148°0'30"E
42°30'30"S
42°31'0"S
Lords
147°59'0"E
147°59'30"E
148°0'0"E
42°31'0"S
42°31'30"S

Figure 3

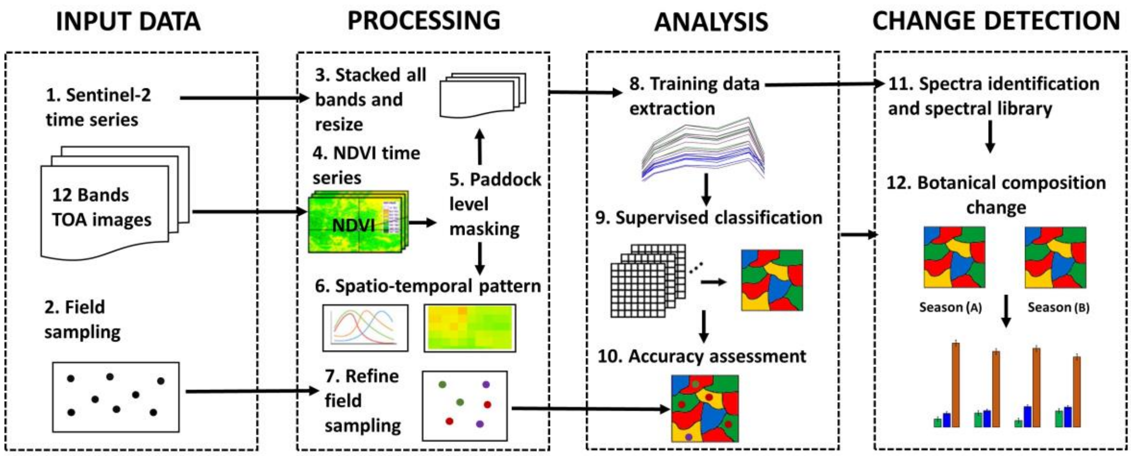

INPUT DATA
PROCESSING
ANALYSIS
CHANGE DETECTION
1. Sentinel-2 time series
12 Bands TOA images
2. Field sampling
3. Stacked all bands and resize
4. NDVI time series
NDVI
5. Paddock level masking
6. Spatio-temporal pattern
7. Refine field sampling
8. Training data extraction
9. Supervised classification
10. Accuracy assessment
11. Spectra identification and spectral library
12. Botanical composition change
Season (A)
Season (B)

Figure 4

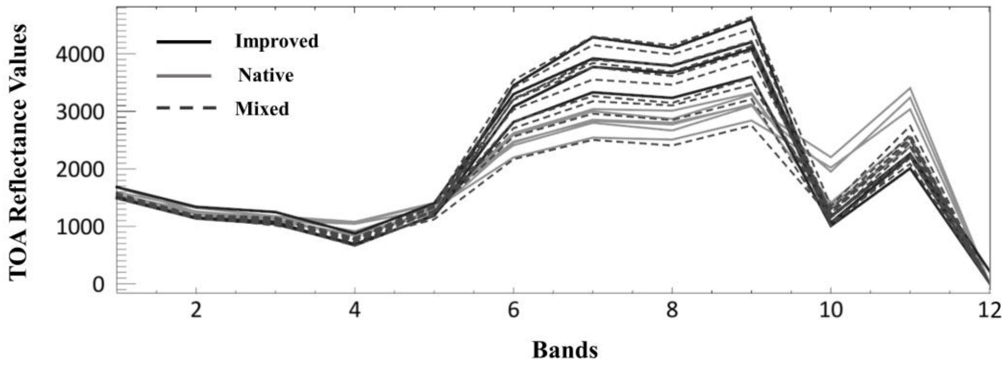
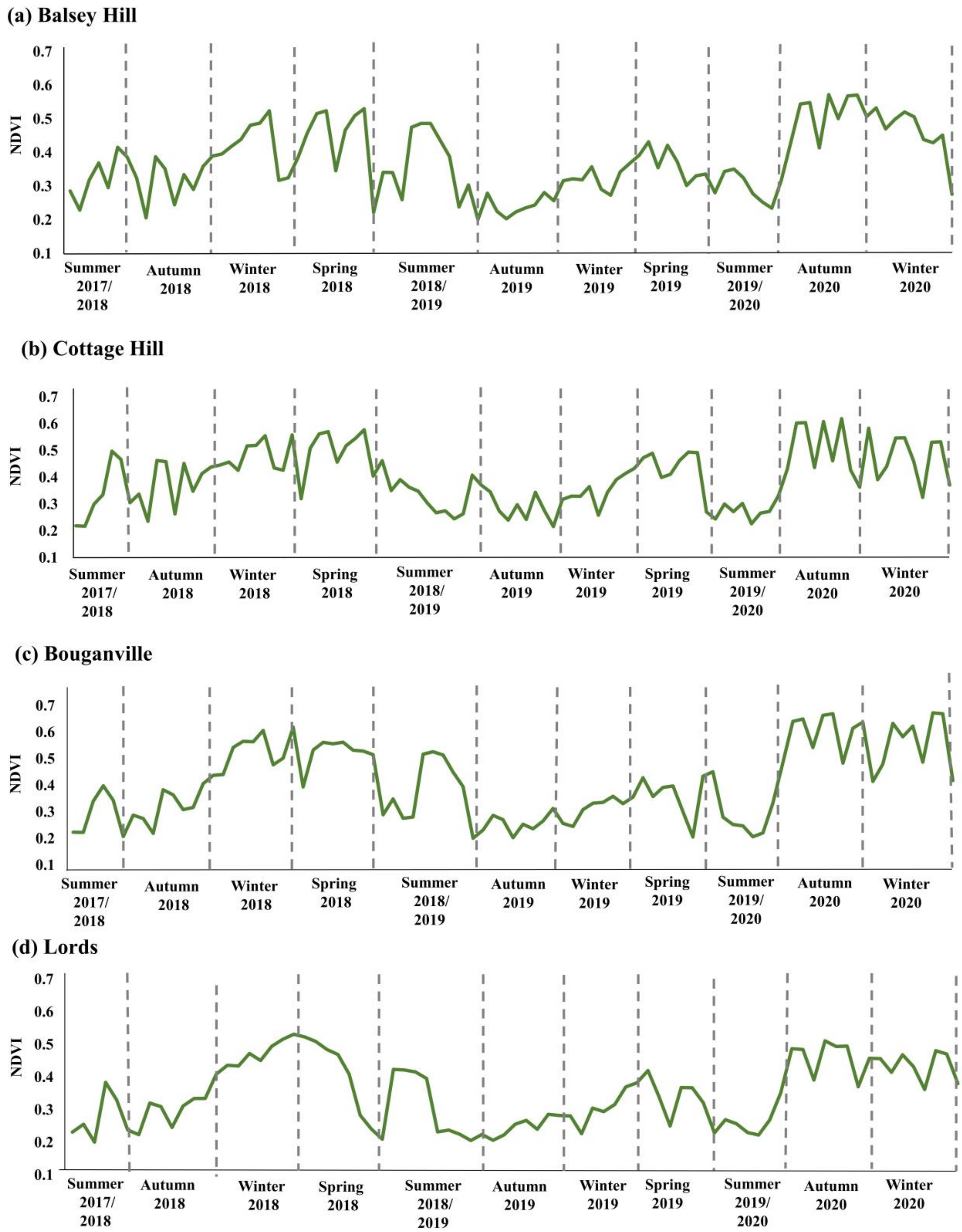
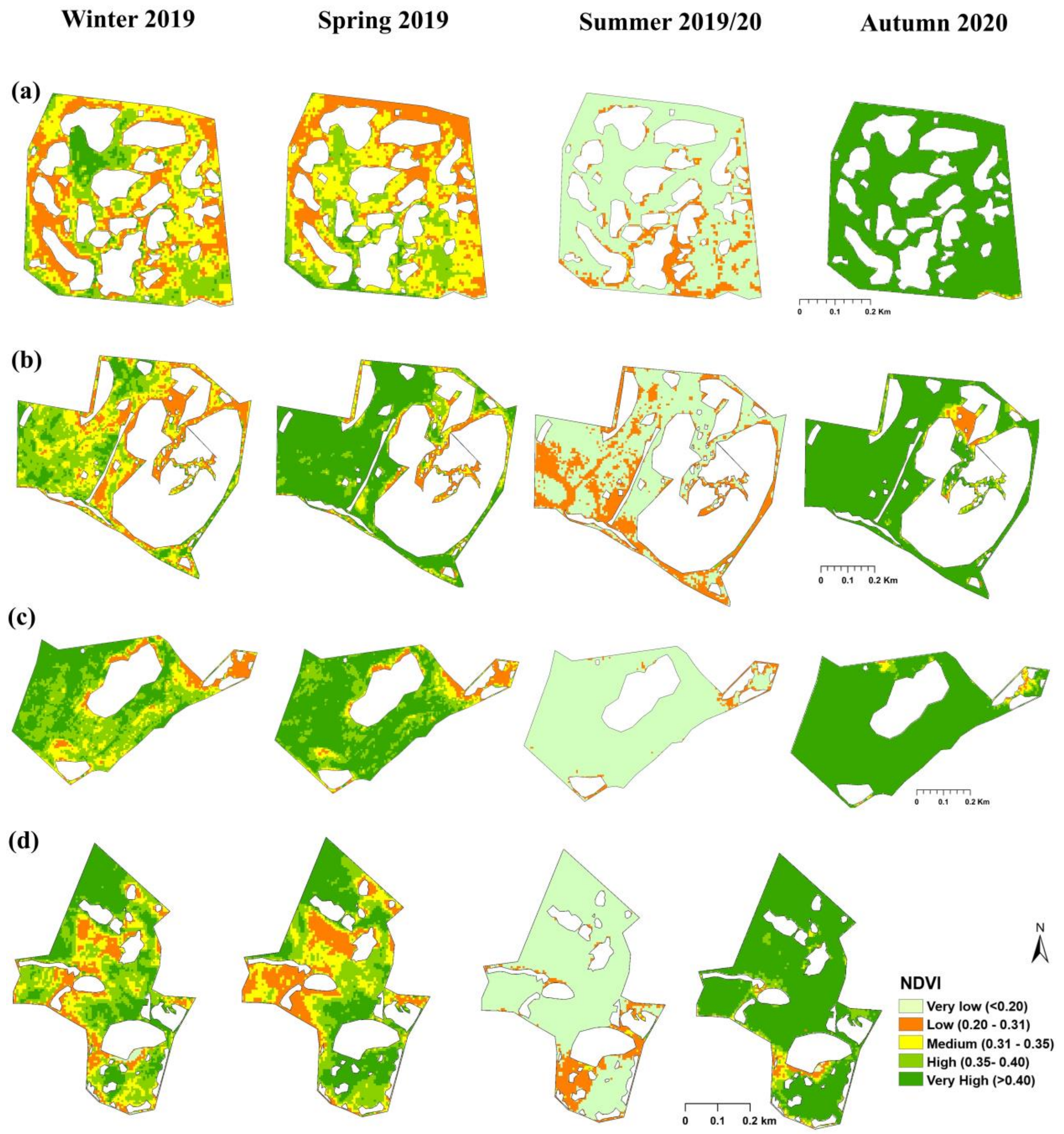

Improved
Native
Mixed
TOA Reflectance Values
4000
3000
2000
1000
0
2
4
6
8
10
12
Bands

Figure 5



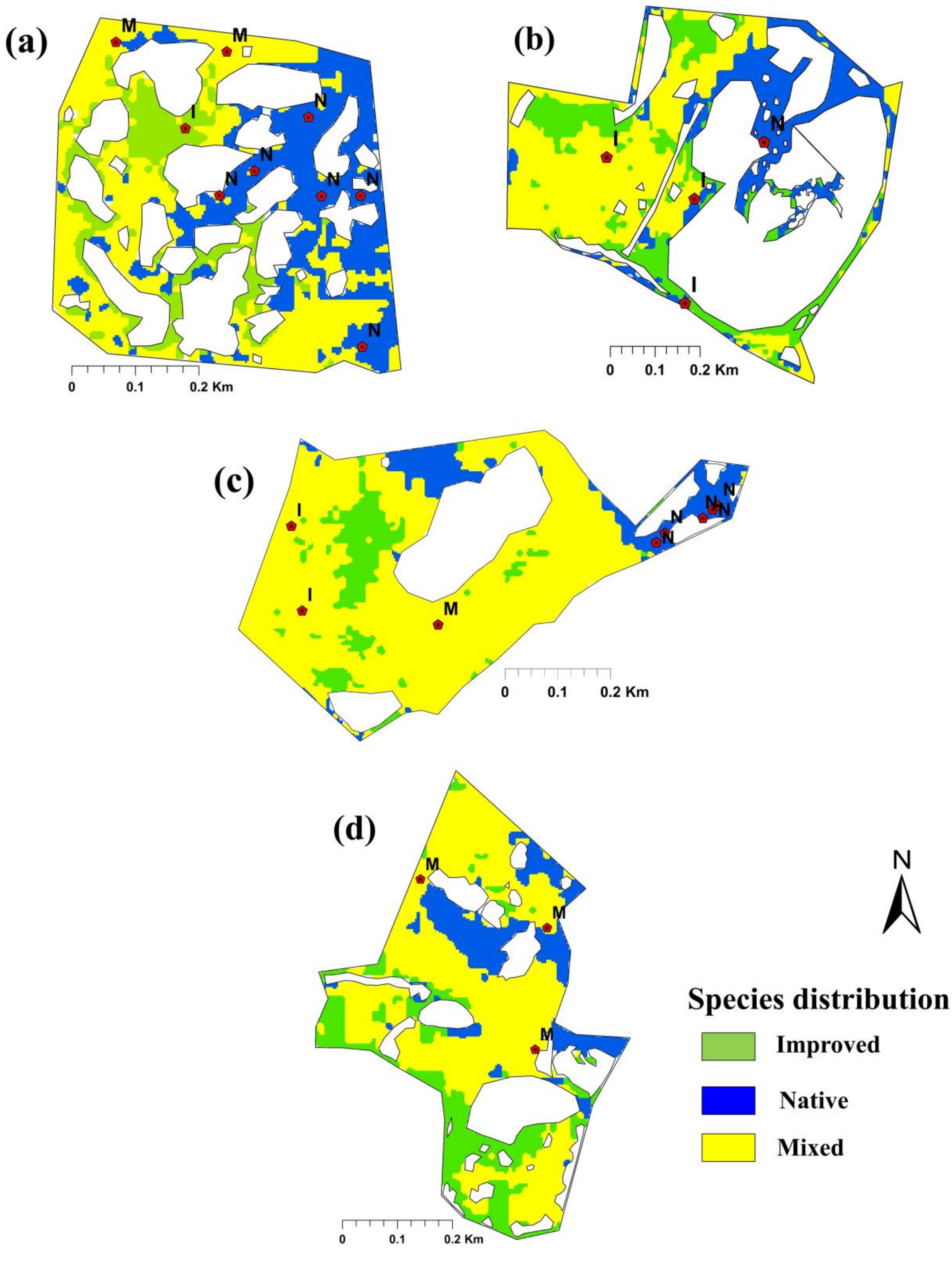
(a) Balsey Hill
(b) Cottage Hill
(c) Bouganville
(d) Lords
NDVI
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Summer 2017/ 2018
Autumn 2018
Winter 2018
Spring 2018
Summer 2018/ 2019
Autumn 2019
Winter 2019
Spring 2019
Summer 2019/ 2020
Autumn 2020
Winter 2020

Figure 6



Winter 2019
Spring 2019
Summer 2019/20
Autumn 2020
(a)
(b)
(c)
(d)
0 0.1 0.2 Km
0 0.1 0.2 Km
0 0.1 0.2 Km
0 0.1 0.2 km
N
NDVI
Very low (<0.20)
Low (0.20 - 0.31)
Medium (0.31 - 0.35)
High (0.35- 0.40)
Very High (>0.40)

Figure 7



(a)
M
M
I
N
N
N
N
N
N
0
0.1
0.2 Km
(b)
N
I
I
I
0
0.1
0.2 Km
(c)
I
I
M
N
N
N
N
N
0
0.1
0.2 Km
(d)
M
M
M
0
0.1
0.2 Km
N
Species distribution
Improved
Native
Mixed

Figure 8

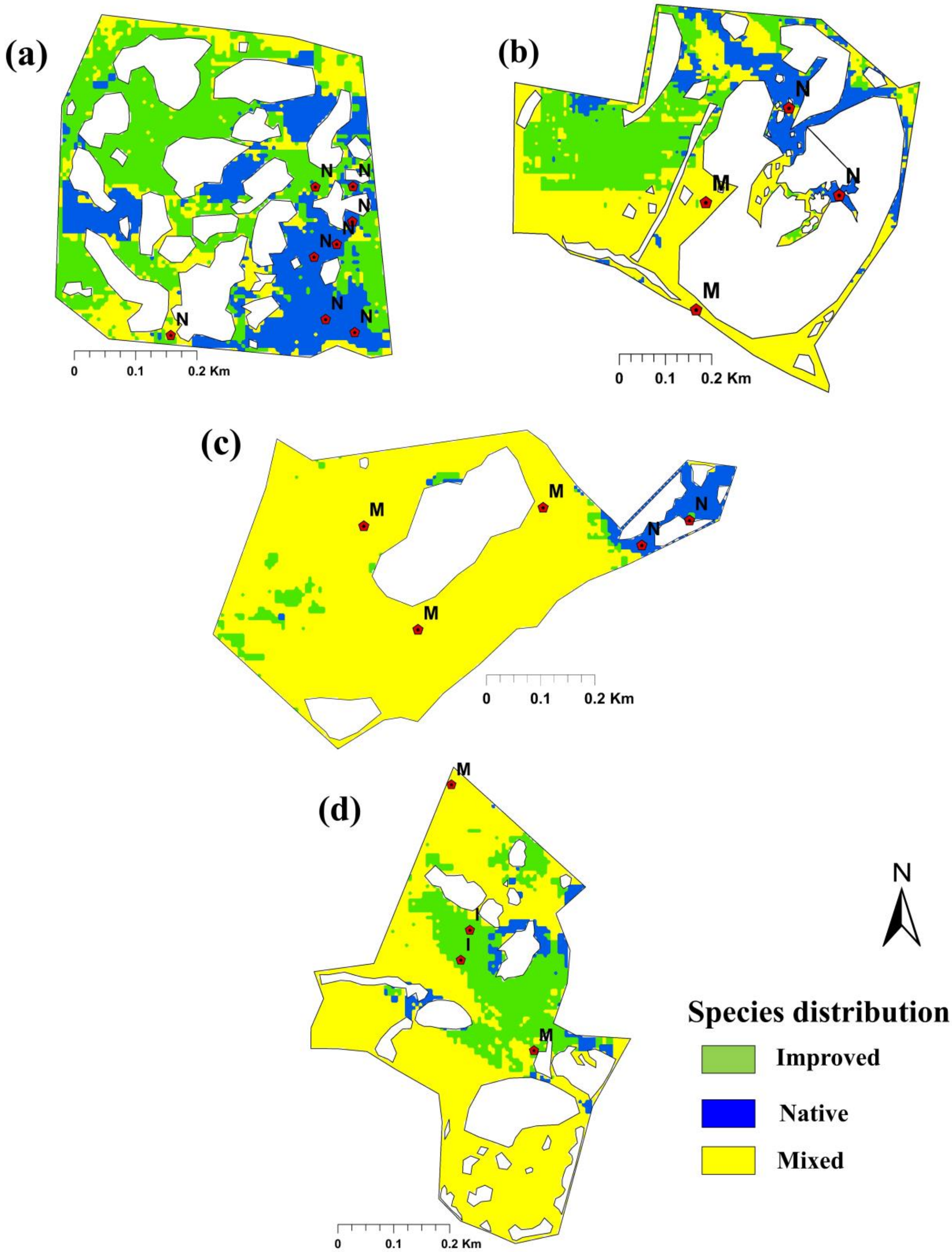
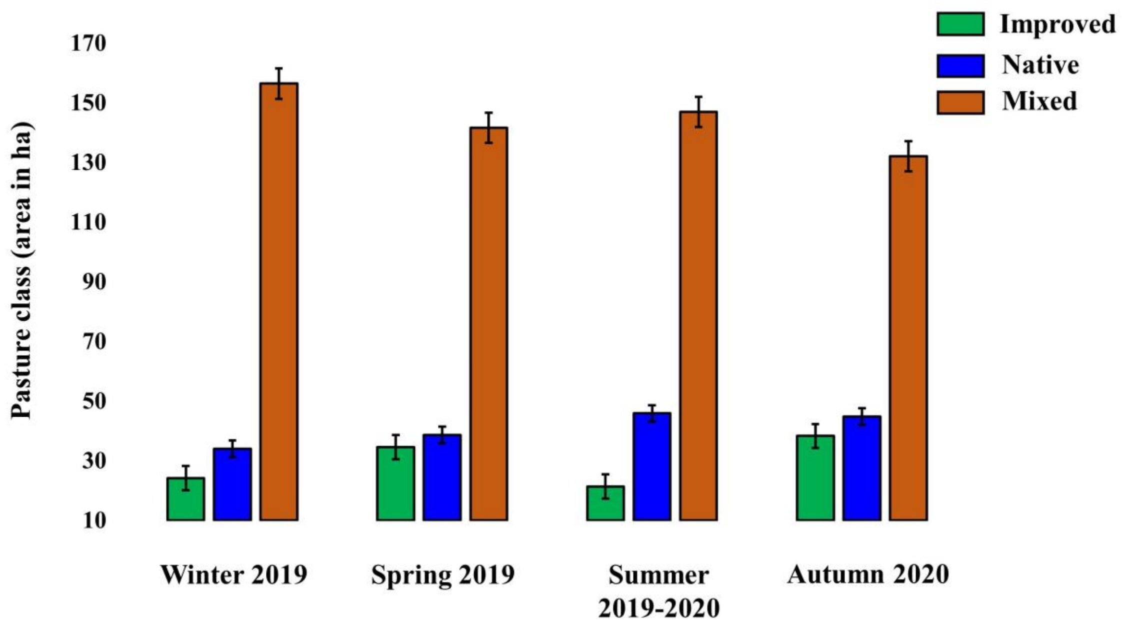

(a)
N
N
N
N
N
N
N
N
N
0
0.1
0.2 Km
(b)
N
N
M
M
0
0.1
0.2 Km
(c)
M
M
M
N
N
0
0.1
0.2 Km
(d)
M
I
I
M
0
0.1
0.2 Km
N
Species distribution
Improved
Native
Mixed

Figure 9


Improved
Native
Mixed
170
150
130
110
90
70
50
30
10
Pasture class (area in ha)
Winter 2019
Spring 2019
Summer
2019-2020
Autumn 2020